Frontier Emerging Technologies, IPO Valuation and Firm Policies

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June 2026

Comments welcome

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Abstract

We develop a dynamic forward-looking text-based measure of firms' engagement with frontier emerging technologies (FETech), using IPO prospectus disclosures. Firms with higher FETech exhibit higher first-day returns, greater trading volume, wider bid-ask spreads, and larger price revisions during bookbuilding, consistent with greater valuation uncertainty, stronger information production, and more intensive price discovery. Beyond IPO pricing, higher FETech predicts higher future liquidity, lower leverage, stronger growth, higher valuation, and more intensive post-IPO innovation activity. These effects are not confined to high-tech firms. After controlling for industry effects using Hoberg and Phillips' (2016) text-based network industries (TNIC3) and using a new TNIC3-based procedure to classify firms into high-tech and non-high-tech groups, we show that these effects hold for both groups. Our findings suggest that engaging with leading emerging technologies is a risky but valuable activity for firms.

Keywords: Emerging Technologies; Gartner Hype Cycle; IPO; Valuation Uncertainty

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1. Introduction

Technology development is an important driver of firm value, industry evolution, and long-run economic growth. At the industry level, the emergence of new technologies can trigger periods of experimentation, entry, and competitive displacement before innovation trajectories mature over the product life cycle (Tushman and Anderson 1986; Klepper 1996). In their early stages, these technologies often feature uncertain commercialization and adoption paths and heterogeneous diffusion timing (Bresnahan and Trajtenberg 1995; Comin and Hobijn 2010), greater dispersion in investor beliefs (Diether, Malloy, and Scherbina 2002), and option-like, nonlinear payoffs tied to growth opportunities (Berk, Green, and Naik 1999).

These characteristics have important implications for capital markets. Firms operating at the technological frontier often derive a substantial portion of their value from growth options rather than assets already in place (Berk, Green, and Naik 1999). The value of these opportunities depends on uncertain future profitability, technological success, and market adoption, especially during periods of technological change (Pástor and Veronesi 2003, 2009). More broadly, heightened uncertainty can discourage or delay investment (Bloom 2009). As a result, firms' engagement with emerging technologies should materially affect valuation dynamics, particularly during episodes of market entry such as IPOs.

The IPO setting provides a particularly revealing context in which to examine how markets price firms' engagement with emerging technologies. IPO firms often lack long operating histories and face severe information asymmetry. Classic models of IPO underpricing attribute first-day returns to adverse selection and information production (Rock 1986;

Benveniste and Spindt 1989). Consistent with this view, empirical studies show that greater ex ante uncertainty is associated with higher underpricing (Ritter 1984; Beatty and Ritter 1986). However, most uncertainty measures used in the IPO literature are indirect proxies, such as firm age, earnings variability, offer size, or textual features of IPO prospectuses (Loughran and McDonald 2013; Crain, Parrino, and Srinivasan 2021), rather than direct measures of firms' engagement with emerging technologies. Therefore, a natural place to look for such measures is the innovation literature, which provides more direct proxies for technological activity.

The innovation literature has traditionally relied on patent-based measures to capture firms' technological activity and positioning. Citation-weighted patent counts and related patent-based indicators have been shown to be informative about firm value and innovation-related growth outcomes (Hall, Jaffe, and Trajtenberg 2005; Kogan et al. 2017). Patent-based metrics, such as patent scope and citation-based indicators such as originality and generality (see, e.g., Lerner 1994; Hall, Jaffe, and Trajtenberg 2001), have also been used to characterize important dimensions of innovation. More recently, Bowen, Frésard, and Hoberg (2023) develop RETech, a text-based measure of a patent's association with a rapidly evolving technological area.

Patent and R&D-based metrics, while powerful, do not capture the full spectrum of firms' engagement with emerging technologies, particularly in the IPO setting, for at least four reasons. First, many firms, particularly in software, digital platforms, fintech, and AI, shy away from using patents to protect their intellectual property (see, e.g., Saidi and Zaldokas 2021) because a patent provides a detailed disclosure of the technology, which invites tinkerers to improve upon it and get new patents. Instead, they prefer to treat their innovation as a trade secret, protected by non-disclosure and non-compete agreements, recognized by courts via inevitable disclosure doctrines. Their innovation may be embodied in proprietary code, data assets, or organizational capital. Second, the growing literature on intangible capital shows that

while intangible investment increasingly shapes firm valuation, it is imperfectly captured by accounting measures or patent data (see, e.g., Lev and Sougiannis 1996; Eisfeldt and Papanikolaou 2013; Peters and Taylor 2017). Third, many firms do not report R&D expenses as a separate item in their financial statements, often for strategic reasons, e.g., to avoid alerting competitors. Consequently, R&D expenses are often missing in financial data (see, e.g., Koh and Reeb 2015), which can limit its usefulness as a measure of innovation input. Finally, many firms doing an IPO are simply too young to have filed for patents.

Consistent with these limitations, in our sample of 2,467 IPO firms from 1994 to 2021, only 53% report R&D, 27% filed patent applications that were eventually granted, and just 25% both report R&D and filed patents before going public. Consequently, a large segment of technologically intensive IPO firms remains outside the scope of patent and R&D-based innovation measures.

To address this gap in the literature, we introduce a dynamic forward-looking measure of firms' engagement with frontier emerging technologies that can be applied to the full universe of IPO firms.[1] We construct FETech, a measure of a firm's engagement with frontier emerging technologies, using Gartner's annual Hype Cycle for Emerging Technologies reports from 1995 to 2021. The Hype Cycle identifies technologies at early stages of commercialization and organizes them within a real-time maturity-and-expectation framework. We use the Gartner Hype Cycle for two reasons. First, it provides a standardized, contemporaneous taxonomy that distinguishes early-stage technologies from those that have already matured, helping align our measurement with what investors could plausibly observe at the IPO rather than with ex post technological success (Fenn and Raskino 2008; Dedehayir

[1] We use the adjectives frontier, leading or cutting-edge interchangeably to refer to the subset of the emerging technologies at a given time that promise to be most impactful.

and Steinert 2016). Second, Gartner-based classifications have been used in prior academic work as an external benchmark for frontier technological activity. For example, Gatchev, Pirinsky, and Venugopal (2022) validate their language-based exploration measure by showing that more exploratory firms are more likely to be involved in technologies identified by Gartner as emerging.

To construct FETech, we focus on technologies identified by Gartner each year as being in the Technology Trigger and Peak of Inflated Expectations stages (see Figure 1), where technologies are still being tested and scaled, expectations are volatile, and commercial outcomes remain highly uncertain. We compile 876 emerging-technology keywords across our sample period and compute FETech as the WF-IDF weighted frequency of these terms in IPO prospectuses. To mitigate concerns that technologies evolve and may cease to be "emerging" over time, we construct time-varying dictionaries so that each IPO firm is evaluated using only technologies classified as emerging within its IPO period, thereby reducing look-ahead bias. FETech therefore captures a firm's engagement in frontier emerging technologies at the time of going public. This Gartner-based classification aligns well with evidence that new breakthrough technologies diffuse gradually and unevenly across the economy. Macro-level research shows that adoption paths are heterogeneous and often require complementary investments before widespread adoption and broader economic effects materialize (see, e.g., Helpman and Trajtenberg 1998; Comin and Hobijn 2010; Kalyani et al. 2025). This diffusion heterogeneity reinforces our premise that firms tied to emerging technologies face greater valuation uncertainty at issuance.

We begin the empirical analysis by validating our FETech measure. We find that IPOs with higher FETech have stronger pre-IPO observable innovation inputs and outputs, including R&D intensity, patent counts, and average citations per patent. In addition, in Table A.2, we provide textual evidence that some firms that do not file patents before IPO offer products and

services related to emerging technology and extensively discuss these technologies in the prospectus. We then examine IPO market outcomes. Consistent with the view that exposure to emerging technologies is linked to greater valuation uncertainty and information asymmetry, IPOs with higher FETech exhibit higher first-day returns, higher first-day trading volume, and wider bid–ask spreads. Economically, a one–standard deviation increase in FETech predicts a 3.78 percentage point increase in the initial return and an 11.8% increase in first-day trading volume, indicating more pronounced price adjustment and information aggregation at listing. We also find that high-FETech IPOs experience larger offer price revisions during bookbuilding, implying more information production and valuation updating prior to setting the final offer price. Together, these results suggest that FETech captures valuation uncertainty and investor disagreement at issuance.

Beyond IPO pricing, we examine whether FETech predicts firms' post-IPO policies, performance, valuation, and innovation activity. We find that higher FETech predicts greater financial slack (higher cash holdings and lower leverage), lower short-run operating profitability, and stronger growth and market valuation (higher Tobin's Q). Consistent with a growth-options interpretation, higher FETech also predicts more intensive post-IPO innovation activity, including higher R&D and stronger patent-based outcomes.

An empirical concern is whether FETech simply proxies for membership in the high technology sector, since firms in industries such as semiconductors, computer software, and biotechnology naturally discuss technological developments in their public disclosures. To address this concern, we employ the TNIC3 industry classification developed by Hoberg and Phillips (2016). This classification has dynamic, product-market-based industry groupings using textual similarity from firm disclosures, providing a more economically grounded alternative to static SIC or NAICS codes. We incorporate TNIC3-based industry-year effects into our empirical models. These controls capture industry-wide factors such as technological

intensity, valuation conditions, and market sentiment within product-market-based peer groups rather than broad industry groups based on the production process such as SIC or Fama and French (1993) industries. That allows us to isolate the effect of firm-specific engagement with frontier emerging technologies.

In addition, we identify high-tech firms using a two-step procedure (described in detail in section 6.1) that combines SIC-based technology industry definitions with TNIC product-market similarity scores, and classify the remaining firms as non-high-tech. We include this high-tech indicator as a control variable in our regressions. Moreover, our main results remain similar when we estimate the models separately for high-tech and non-high-tech subsamples. These TNIC3-based controls and non-high-tech subsample analyses suggest that our results are not merely a high-tech sector effect; rather, they capture firm-level variation in engagement with frontier emerging technologies among firms competing in a similar product-market space.

Our main findings are robust to the inclusion of a broad set of additional controls. In particular, the results remain economically and statistically similar after controlling for traditional innovation proxies, including R&D intensity, patent counts, and citations per patent, as well as text-based measures of innovation and prospectus sentiment. We also account explicitly for IPO market conditions at the industry level using lagged TNIC3-based measures constructed from prior IPO activity. These variables capture time-varying 'hot IPO market' and valuation conditions within the firm's product-market industry, alleviating concerns that our findings are driven by cyclical issuance environments rather than firm-specific engagement with emerging technologies.

We further examine heterogeneity in the relation between FETech and IPO outcomes by interacting FETech with key firm characteristics that proxy for information environment and certification, including firm size, firm age, patent possession, and venture-capital (VC)

backing. Across these interaction specifications, the baseline relation between FETech and IPO price-discovery outcomes remains statistically significant and economically meaningful, suggesting that our main findings are not confined to any single subgroup of IPO firms. Overall, these results support the interpretation that FETech captures firm-specific engagement with emerging technologies that is relevant for IPO valuation uncertainty and market pricing, rather than merely reflecting a narrow set of patenting, VC-backed, large, or mature issuers.

We contribute to multiple strands of literature. First, we extend the innovation literature by introducing a measure of firms' engagement with frontier emerging technologies based on IPO prospectus text, allowing us to capture this activity among young firms at the time they enter public markets. This approach complements prior text-based measures of innovation developed primarily for seasoned public companies from other corporate disclosures (see, e.g., Bellstam, Bhagat, and Cookson 2021; Li et al. 2021). Second, our measure adds to other recent language-based approaches that seek to identify exploratory and innovative activity using textual data (e.g., Gatchev, Pirinsky, and Venugopal 2022).

Third, our study contributes to the growing literature showing that patenting is an incomplete proxy for innovation. Instead of patenting, some firms monetize their innovation via lead time advantages; complementary capabilities; or by closely guarding their innovation as trade secrets, protected by contracts (e.g., non-disclosure and non-compete agreements) and legal doctrines such as inevitable disclosure (see, e.g., Teece 1986; Harabi 1995; Arundel 2001; and Saidi and Žaldokas 2021). Text-based methods can capture innovative activity that is not fully reflected in patent or R&D data (see, e.g., Bellstam, Bhagat, and Cookson 2021). FETech does not require firms to separately report R&D or to hold patents, allowing us to measure IPO firms' engagement with leading emerging technologies regardless of how the technology is protected.

Finally, because engagement with emerging technologies is closely associated with valuation uncertainty and information asymmetry, our paper also contributes to the IPO literature that uses textual disclosures to study uncertainty, information production, and price formation (e.g., Loughran and McDonald 2013; Crain, Parrino, and Srinivasan 2021), by showing that engagement with cutting-edge emerging technologies helps explain cross-sectional variation in IPO outcomes (such as underpricing, price revision, initial trading volume, and bid-ask spreads), and future financial policies (such as cash holdings), growth and valuation.

2. Hypothesis Development

FETech captures a firm's engagement with frontier emerging technologies by quantifying the extent to which its IPO prospectus discusses technologies classified by Gartner's Hype Cycle as being in the Technology Trigger through Peak of Inflated Expectations stages (see Figure 1). Frontier emerging technologies are advanced technological domains that remain early in their commercialization life cycle and are expected to reshape products, services, business processes, or business models, but whose applications and adoption paths remain unsettled. Because such technologies are still commercially immature, firms associated with them typically face uncertain adoption, evolving use cases, and substantial complementary investment needs before their commercial potential can be fully realized (Teece 1986; Helpman and Trajtenberg 1998). As a result, firms engaged with cutting-edge emerging technological domains face a wider distribution of future outcomes than firms operating in more mature technological areas, since uncertainty about the productivity and eventual adoption of new technologies is central to their valuation (Pástor and Veronesi 2009).

Although engagement with leading emerging technologies can create substantial growth opportunities, it also introduces greater uncertainty for both firms and investors than engagement with mature technological domains. Early-stage technologies are characterized by uncertain timing of adoption, uncertain market size, and uncertain competitive trajectories. Financing such activities can therefore be costly because outside investors face difficulty assessing both the probability of success and the magnitude and timing of future payoffs, which raises adverse-selection frictions and the cost of external finance (Myers and Majluf 1984; Brown, Fazzari, and Petersen 2009). In IPO settings, where valuation is formed under severe information asymmetry, this uncertainty is especially important. Classic theories of IPO underpricing imply that asymmetric information and investor information production can lead issuers and underwriters to price IPOs conservatively (Rock 1986; Benveniste and Spindt 1989). Consistent with this view, empirical evidence shows that IPOs subject to greater ex ante uncertainty and more risk disclosure in prospectus text exhibit higher underpricing (see, e.g., Beatty and Ritter 1986; Loughran and McDonald 2013). Therefore, we hypothesize that IPOs of firms with greater engagement with frontier emerging technologies, as measured by higher FETech, will exhibit higher initial returns because issuers and underwriters price these IPOs more conservatively in the presence of heightened valuation uncertainty and information asymmetry.

H1. IPO firms with greater engagement with frontier emerging technologies, as measured by higher FETech, exhibit higher initial returns.

Uncertainty about a firm's prospects also has implications for secondary-market trading and liquidity. Kravet and Muslu (2013) show that more extensive risk discussion in 10-K filings predicts higher trading volume around the filing date. Azimi and Agrawal (2021) further show that uncertainty reflected in disclosure language increases information asymmetry and divergence of investor beliefs, leading to greater trading activity. In the IPO setting, greater

uncertainty should similarly intensify price discovery in the early aftermarket. At the same time, higher valuation uncertainty raises adverse-selection risk and liquidity provision costs, which should be reflected in wider bid-ask spreads. Prior work also links IPO uncertainty to aftermarket liquidity frictions and wider spreads (Hribar 2004; Guo, Lev, and Zhou 2004; Ellul and Pagano 2006; Barth et al. 2017). Given the elevated uncertainty associated with frontier emerging technologies, we hypothesize that IPOs with higher FETech will have higher initial trading volume and wider bid-ask spreads.

H2. IPO firms with greater engagement with frontier emerging technologies, as measured by higher FETech, exhibit higher initial trading volume.

H3. IPO firms with greater engagement with frontier emerging technologies, as measured by higher FETech, exhibit wider bid-ask spreads.

Valuation uncertainty should also affect the bookbuilding process. In bookbuilding models, the underwriter learns about investor demand and valuation through indications of interest, and this information is incorporated into the final offer price (Benveniste and Spindt 1989). When valuation uncertainty is greater, the information revealed during bookbuilding becomes more valuable, leading underwriters to revise the offer price more aggressively as investor feedback arrives. Hanley (1993) shows that offer price revisions reflect information learned during the bookbuilding process. Given the elevated uncertainty associated with frontier emerging technologies, we hypothesize that IPOs with higher FETech will experience larger offer price revisions during bookbuilding.

H4. IPO firms with greater engagement with frontier emerging technologies, as measured by higher FETech, exhibit larger offer price revisions during bookbuilding.

Engagement with leading emerging technologies is likely to have implications beyond IPO pricing. Because these technologies require experimentation, complementary investments,

and strategic flexibility, firms associated with them may have stronger incentives to preserve financial slack after going public. Prior research shows that uncertainty indicated by textual sentiment is associated with higher future cash holdings (Azimi and Agrawal 2021). In addition, firms operating in product markets with uncertain structures may hold more cash in order to maintain flexibility for future innovative investment (Lyandres and Palazzo 2016). Given the elevated uncertainty and financing needs associated with frontier emerging technologies, we hypothesize that IPOs with high FETech will hold more cash in the future.

H5. *IPO firms with greater engagement with frontier emerging technologies, as measured by higher FETech, hold more cash in the future.*

Finally, engagement with cutting-edge emerging technologies may also reflect stronger future growth opportunities. Bellstam, Bhagat, and Cookson (2021) show that more extensive discussion of innovation predicts higher firm growth opportunities. Firms with stronger growth opportunities should subsequently experience faster growth and command higher valuations. If FETech captures economically meaningful engagement with emerging technological domains, then firms with higher FETech should display stronger post-IPO growth prospects and greater market valuation. Given the growth opportunities associated with engagement with frontier emerging technologies, we hypothesize that IPOs with high FETech will exhibit higher future growth rates and higher Tobin's Q.

H6. *IPO firms with greater engagement with frontier emerging technologies, as measured by higher FETech, exhibit higher future growth rates and higher Tobin's Q.*

3. Measurement of FETech

We construct FETech using Gartner's *Hype Cycle for Emerging Technologies* reports from 1995 to 2021. Gartner is a widely recognized technology advisory firm, and its Hype Cycle is a widely used framework that positions technologies along an expectations curve intended to reflect their stage of development, adoption, and commercialization (Steinert and Leifer 2010; Dedehayir and Steinert 2016; Shi and Herniman 2023). Because our objective is to measure firm engagement with leading technologies at early stages of technological development—where uncertainty about feasibility, adoption, and commercial impact is especially high—we focus on technologies located on the left side of the Hype Cycle, specifically those in the Technology Trigger and Peak of Inflated Expectations phases. Figure 1 illustrates how we construct FETech. We collect and standardize the technology names appearing in these reports by removing duplicates, harmonizing spelling and hyphenation, and consolidating closely related variants. This process yields 876 unique technology keywords and phrases, which form the basis of our frontier emerging technology dictionaries. Table A1 reports the technology keywords used to construct our dictionaries.

A key concern in using any emerging-technology list is that emerging status is inherently time-varying. Technologies follow their own life cycles, and terms classified as emerging in one period may become mainstream, decline in relevance, or disappear within a few years. To ensure that FETech reflects contemporaneous technological positioning, we construct dynamic (time-varying) dictionaries by partitioning the 876 technology terms into five windows: 1995–2000, 2001–2005, 2006–2010, 2011–2015, and 2016–2021. Each dictionary contains only those technology keywords that Gartner classified on the left side of the Hype Cycle during the corresponding window. For example, the 1995–2000 dictionary includes only those technologies that appeared in Gartner's Technology Trigger or Peak of Inflated Expectations phases during that interval. This design ensures that, for an IPO occurring

in a given period, FETech is computed using only technologies that were contemporaneously viewed as emerging, thereby reducing measurement error that would arise from treating older, already mature technologies as "emerging" for later IPOs.

Before counting emerging-technology terms, we preprocess both the IPO prospectus text and the dictionary terms following standard practice in textual analysis. We clean the prospectus corpus to remove non-informative components and improve comparability across documents, then remove stop words, tokenize the text into words, and convert tokens into n-grams. The n-gram construction is important because many technologies are expressed as multi-word phrases (e.g., "machine learning," "deep neural network", and "wireless technology"), which would be missed or mismeasured using unigram counts alone. We apply the same preprocessing rules to both the prospectuses and the dictionary terms so that dictionary matching captures the intended technological expressions with minimal noise.

Using the processed texts, we measure, for each IPO firm, the frequency with which the emerging-technology terms from the appropriate time-window dictionary appear in its prospectus. This step yields a raw count of emerging-technology language aligned with the firm's IPO period. However, simple word counts may overweight terms that are common across many prospectuses and underweight terms that are more distinctive. To address this concern, we compute FETech using a log-normalized term frequency–inverse document frequency weighting scheme (WF-IDF). WF applies log normalization to within-prospectus term frequency, reducing sensitivity to repeated mentions of the same term within a prospectus, while IDF downweights terms that appear in many prospectuses and therefore carry less discriminatory information about a firm's technological engagement.

Finally, we define FETech for firm i as the document length-scaled sum of WF-IDF weights for all emerging-technology terms in the time-varying Gartner dictionary applicable to the firm's IPO period:

$$\text{FETech}_i = 100 \times \frac{1}{L_i} \sum_{k \in D(t_i)} \text{WF}_{ik} \times IDF_{kt_i},$$

where

$$\text{WF}_{ik} = \begin{cases} 1 + \ln(f_{ik}), & \text{if } f_{ik} > 0, \\ 0, & \text{if } f_{ik} = 0, \end{cases}$$

and

$$\text{IDF}_{kt} = \ln\left(\frac{N_t}{df_{kt}}\right).$$

Here, L_i is the total number of words in firm i's prospectus after preprocessing, $D(t_i)$ denotes the time-varying Gartner dictionary corresponding to firm i's IPO window t_i, and f_{ik} is the number of occurrences of term k in firm i's prospectus. N_t is the number of IPO prospectuses in window t, and df_{kt} is the number of prospectuses in the window t in which term k appears at least once, so the IDF component is computed within the IPO's dictionary window. We compute IDF only for terms with $df_{kt} \geq 1$; terms that never appear in the prospectus corpus contribute zero to FETech because $f_{ik} = 0$ for all i. Thus, FETech is computed as the WF-IDF weighted intensity of emerging-technology terms in the prospectus, expressed as a percentage. This construction ensures comparability across prospectuses of different lengths and captures the intensity of emerging-technology discussion rather than the absolute quantity of text.

4. Data sources, summary statistics and correlations

4.1 Data sources and summary statistics

We collect S-1 registration statements for U.S. IPO issuers from 1994 to 2021 using the WRDS–SEC Analytics Suite and direct downloads from SEC EDGAR. Following standard IPO sample construction procedures, we exclude REITs, ADRs, closed-end funds, and offerings priced below $5 per share. These screens yield a final sample of 2,467 IPOs. We obtain deal-level pricing variables, including the offer price and offer-price revision, from SDC Platinum, and we collect aftermarket trading outcomes, including the first-day closing price, trading volume, and bid-ask spread, from CRSP. Firm fundamentals and the remaining control variables are drawn from Compustat. We define Top Underwriter using underwriter reputation rankings from Jay Ritter's website, and we obtain the patent data used to validate our innovation measures from Noah Stoffman's website. Table 1 reports descriptive statistics for the main variables, with definitions provided in Table A.3. Our key explanatory variable is FETech. The summary statistics reported in Table 1 are broadly similar to those documented in prior studies that analyze the text in IPO prospectuses (e.g., Hanley and Hoberg 2010; Loughran and McDonald 2013; Crain, Parrino, and Srinivasan 2021).

4.2. Correlations

Table 2 reports pairwise correlations among the main variables. FETech is positively and significantly correlated with key IPO price-discovery outcomes, including first-day return, price revision, trading volume, and bid-ask spread. It is also positively related to conventional innovation proxies, such as patent counts, citations per patent, and R&D intensity, but these correlations are modest in magnitude. Consistent with Bowen, Frésard, and Hoberg (2023), the latter correlations are economically small (0.05, 0.06, and 0.11, respectively), indicating that

FETech captures dimensions of engagement with frontier emerging technologies that are distinct from standard patent and R&D-based measures.

5. Empirical results

5.1 Validation of FETech

To validate our measure of leading emerging technologies, we follow the approach of Li et al. (2021) and Kogan et al. (2017) and estimate validation regressions in which standard innovation proxies (e.g., patent counts, citations per patent and R&D intensity) serve as the dependent variables. We obtain patent data from Kogan et al. (2017), updated through 2020, and restrict the patent measures to patents filed prior to the IPO offer date so that the validation draws only on pre-IPO information. Table 3 reports the results. Across all three specifications, the coefficients on FETech are positive and statistically significant. These findings suggest that firms with greater emerging-technology engagement in their IPO prospectuses also exhibit stronger observable pre-IPO innovation inputs and outputs.

5.2 FETech and IPO outcomes

We next examine the relation between FETech and four IPO outcomes—first-day return, first-day trading volume, first-day bid-ask spread, and price revision—and report the results in Table 4. In each set of regressions, the key explanatory variable is FETech. Following the typical specification in the IPO literature, our baseline controls include High-tech, Top Underwriter, VC Backing, Positive EPS, Market Return, Share Overhang, and the natural logarithms of Firm Age and Sales. We also include Up Revision as a control except in the price revision regression. In addition, all the regressions include the industry effect, which is the mean of the dependent variable for a firm's text-based network industry (TNIC3), following the procedure in Hoberg and Phillips (2016).

In column (1) of Table 4, the coefficient on FETech is positive and statistically significant across specifications. Economically, a one-standard-deviation increase in FETech (0.015) predicts a 3.78 percentage-point (0.015 × 251.716) increase in first-day return, which is substantial compared to its median value of 10.53. This evidence supports H1, which predicts that IPO firms with greater engagement with frontier emerging technologies exhibit higher initial returns. The result is consistent with greater valuation uncertainty and information asymmetry for high-FETech issuers, leading issuers and underwriters to set offer prices more conservatively at the time of listing.

Column (2) shows that FETech positively predicts offer price revision. A one-standard-deviation increase in FETech predicts a 0.98 percentage-point higher price revision. This result supports H4, which predicts that IPO firms with greater engagement with frontier emerging technologies exhibit larger price revisions during bookbuilding. This finding indicates that underwriters revise the offer price more aggressively when valuing high-FETech issuers, consistent with greater uncertainty and more informative investor feedback during the bookbuilding process.

Columns (3) and (4) indicate that FETech also positively predicts aftermarket trading activity and liquidity conditions. A one-standard-deviation increase in FETech predicts an 11.8 percent (exp [0.015 × 7.418] − 1) increase in trading volume and a 0.64 percentage-point increase in the bid-ask spread. These findings support H2 and H3, which predict that IPO firms with greater engagement with frontier emerging technologies exhibit higher initial trading volume and wider bid-ask spreads. Higher trading volume is consistent with more intensive price discovery and greater dispersion in investor beliefs while the wider bid-ask spread is consistent with greater information asymmetry and higher liquidity provision costs in the early aftermarket.

5.3 Post-IPO firm policies, performance, valuation and innovation activities

We next examine whether a firm's engagement with leading emerging technologies at the time of the IPO predicts its future financial policies, operating performance, valuation, and innovation activities in the year following the IPO. We focus on two financial policies that are likely to be affected by a firm's engagement with frontier emerging technologies: leverage and liquidity. Projects involving frontier emerging technologies are typically characterized by substantial uncertainty and low collateral value. Such projects are therefore more naturally financed with equity or internally generated cash rather than debt (see, e.g., Myers 1977; Titman and Wessels 1988). This reasoning implies that firms with higher FETech should operate with lower leverage. Firms with higher FETech may also hold more cash to preserve financial flexibility and finance risky innovation projects (see, e.g., Lyandres and Palazzo 2016), implying higher cash holdings. Because engagement with frontier emerging technologies often involves long-horizon investment projects, and because R&D expenditures are expensed rather than capitalized, firms with higher FETech may exhibit lower short-run accounting profitability, as measured by return on assets (ROA). At the same time, if these projects create valuable future growth opportunities, firms with higher FETech should command higher market valuations, as measured by Tobin's Q. Finally, we expect firms with higher FETech to exhibit greater innovation input, measured by R&D, and greater quantity, quality, and value of innovation output, measured by the number of patents and average citations per patent.

We report the regressions for each dependent variable in Table 5. Consistent with these predictions, we find that FETech negatively predicts leverage and ROA and positively predicts cash holdings. We also find that FETech positively predicts future sales growth and Tobin's Q. Finally, consistent with our expectations, FETech positively predicts future R&D, patent counts, and patent quality.

6. Robustness and identification

6.1 Tests on subsamples of technology and non-technology firms

Although FETech is designed to capture firms' engagement with emerging technologies, a natural concern is that high FETech may simply proxy for whether a firm operates in a high-tech sector. To address this concern, we define high-tech firms using a two-step procedure that combines SIC-based classification with text-based product-market similarity from Hoberg and Phillips (2016). First, we construct a set of base high-tech firms using SIC codes: firms are classified as high-tech if their four-digit SIC code falls into the high-tech industries defined in Loughran and Ritter (2004, Appendix D). We expand this base set by additionally including firms in SIC 283 (Drugs) and SIC 38 (Measuring, Analyzing, and Controlling Instruments), while excluding firms in SIC 386 (Photographic Equipment and Supplies) and SIC 387 (Watches and Clocks). Second, we broaden the high-tech group to include firms outside the base SIC list that operate in the same product space. Using TNIC product-market similarity scores, we compute, for each non-base firm-year, the average TNIC similarity score relative to base high-tech firms and classify a firm as high-tech if this average similarity lies in the top decile of the distribution.[2] Our final high-tech indicator equals one for firms in either the base SIC set or the TNIC-expanded set, and zero otherwise.

Table 6 reports results from regressions analogous to our baseline specifications, estimated separately for the high-tech subsample (Panel A) and the non-high-tech subsample (Panel B). As expected, the coefficients on FETech in Panel A are positive and statistically significant, consistent with our full-sample findings. Importantly, the estimates in Panel B are similar in both sign and statistical significance. These results alleviate the concern that FETech simply captures technology-sector membership. In other words, FETech predicts IPO outcomes within both high-tech and non-high-tech firms, consistent with the idea that FETech captures

[2] We thank Jerry Hoberg for suggesting this procedure.

firm-level engagement with frontier emerging technologies disclosed in the IPO prospectus rather than simply identifying firms that belong to traditional high-tech sectors (or firms closely linked to those sectors through product-market similarity).

6.2 Additional controls

6.2.1 Innovation controls

We find that an IPO firm's engagement with emerging technologies, measured by FETech, positively predicts its first-day return, trading volume, bid-ask spread, and offer price revision. We next examine whether these relations are robust to the inclusion of traditional measures of innovation. Accordingly, we augment regressions similar to those in Table 4 with controls for pre-IPO patenting activity, including the number of patents filed prior to the IPO offer date and average citations per patent, as well as a text-based innovation measure constructed following Li et al. (2021).

In Table 7, across all four specifications, the coefficient on FETech remains positive and statistically significant, indicating that FETech captures economically meaningful variation in IPO price-discovery outcomes beyond what is reflected in patenting activity, citation-based innovation quality, or broader innovation-related language in disclosures. These results suggest that firms with higher emerging-technology engagement face greater valuation uncertainty and information frictions, which are consistent with higher initial returns, greater trading volume, and wider bid-ask spreads, as well as more intensive valuation updating during bookbuilding, as reflected by larger offer price revisions.

6.2.2 IPO cycle controls

Next, following Hsu et al. (2010) and Yung, Çolak, and Wang (2008), we further control for IPO-cycle conditions at the industry level. Using TNIC3-based product-market industries,

we construct three lagged measures that capture time-varying issuance "hotness" and valuation conditions within each IPO firm's industry. Specifically, we compute the average IPO underpricing and average market-to-book ratio, respectively, for IPOs in the firm's TNIC3 industry, measured over the prior IPO year. We also compute the number of IPOs in the firm's TNIC3 industry during the previous quarter. These TNIC3-based IPO-cycle controls absorb fluctuations in industry-level sentiment and issuance activity and ensure that our estimates for FETech are not driven by cyclical IPO market conditions. After including these controls, in Table 8, the coefficient on FETech remains positive and statistically significant across all specifications, indicating that our main results are not attributable to industry-level IPO hotness or time-varying issuance conditions.

6.2.3 Sentiment Controls

In addition, to control for the tone of IPO disclosures, we include negative and positive sentiment measures constructed using the word-count approach of Loughran and McDonald (2011). Table 9 presents the results. Across all four regressions in each panel, the coefficients on FETech remain positive and statistically significant. These findings indicate that FETech captures emerging technology engagement, and the associated valuation uncertainty, beyond what is reflected in the general sentiment of the prospectus. The results are similar when both positive and negative sentiment are included simultaneously in the regressions, so we omit those estimates for brevity.

6.3 Tests excluding IPO firms in technology bubble and financial crisis

Loughran and Ritter (2004) document that IPO pricing outcomes exhibit unusually extreme behavior during the peak of the technology bubble in 1998–1999, and IPO market conditions were also highly atypical during the financial crisis years 2008–2009. Because

observations from these periods may exert disproportionate influence, we assess whether our results are driven by these episodes. Table 10 reports estimates corresponding to our baseline after excluding IPOs issued during 1998–1999 and 2008–2009. The results remain generally similar to our baseline findings, indicating that our conclusions are not driven by these extreme market periods.

6.4 Cross-sectional tests

Our baseline results suggest that IPOs with higher FETech are characterized by greater valuation uncertainty and information frictions, as reflected in higher first-day returns, trading volume, and bid-ask spreads, and they also exhibit stronger demand revelation during bookbuilding, as reflected in larger offer price revisions. A natural hypothesis is that the incremental uncertainty associated with emerging-technology engagement should be attenuated for firms with stronger information environments or external certification, e.g., firms that are older, larger, have pre-IPO patents, or are VC-backed.

To test this notion, we perform heterogeneity analyses using interaction specifications. We first construct a binary indicator Old, equal to one if the IPO firm's age is above the sample median and zero otherwise. We then re-estimate our baseline regressions from Table 4 by adding Old and the interaction term Old × FETech, and report the results in Panel A of Table 11. In this panel, the coefficients on Old × FETech are statistically insignificant in all four IPO outcome regressions. These estimates indicate that the effect of FETech on first-day return, price revision, trading volume, and bid-ask spread is not significantly different between older and younger issuers. Thus, we do not find evidence that firm age materially attenuates the relation between emerging technology engagement and IPO outcomes.

We then define an indicator Large that equals one for IPO firms whose total assets are above the sample median and zero otherwise. Following the same approach as in Panel A, we re-estimate our baseline regressions after adding Large and the interaction term Large × FETech and report the results in Panel B of Table 11. In these regressions, coefficients of the interaction term are statistically insignificant, indicating that the effect of FETech on the IPO outcomes is not statistically different between smaller and larger issuers.

We then define Has Patents as an indicator equal to one if the issuer has at least one patent filed before the IPO offer date, and zero otherwise. Using the same interaction approach as in Panel A, we re-estimate the baseline regressions including Has Patents and Has Patents × FETech, with results reported in Panel C of Table 11. The interaction term is not statistically significant, implying that the effect of FETech on IPO outcomes is statistically indistinguishable between firms with and without pre-IPO patents.

Lastly, we create a binary variable VC that equals one if the IPO firm is venture-capital backed and zero otherwise. Panel D of Table 11 reports results from regressions that augment the baseline models with VC and the interaction term VC × FETech. The interaction term indicates that the effect of FETech is smaller for VC-backed firms in predicting price revision, although the estimate is statistically significant only at the 10% level. This pattern supports the idea that VC participation can partially substitute for bookbuilding-based price updating; for example, Jeppsson (2018) shows that venture-capital insider participation during the IPO process is associated with smaller offer price revisions. Across all four regressions, the main effect of FETech remains positive and statistically significant in each of the four IPO outcome regressions. Overall, the results show that the pricing effects of FETech are not driven by any single subgroup of firms, reinforcing the view that engagement with cutting-edge emerging technologies is a distinct and broadly important source of IPO valuation uncertainty.

7. Conclusion

This paper introduces FETech, a forward-looking text-based measure of firms' engagement with frontier emerging technologies, using IPO prospectus disclosures and Gartner's Hype Cycle classifications. Our main results show that firms with higher FETech experience higher first-day returns, greater trading volume, wider bid-ask spreads, and larger offer price revisions during bookbuilding. These findings indicate that engagement with leading emerging technologies is associated with greater valuation uncertainty, stronger information production, and more intensive price discovery at the IPO. Beyond the IPO itself, we find that firms with higher FETech subsequently hold more cash, use less leverage, exhibit lower short-run accounting profitability, and display stronger future growth, higher Tobin's Q, and more intensive innovation activity.

A central contribution of the paper is to show that FETech captures firm-specific technological involvement rather than merely broad technology-sector membership. We show that the relation between FETech and IPO outcomes remains statistically significant after controlling for TNIC3-based industry effects, which absorb industry-level technological intensity, valuation conditions, and sentiment within narrowly defined product-market peer groups. We further show that the pricing effects of FETech hold separately within both high-tech and non-high-tech subsamples constructed using a combined SIC- and TNIC similarity–based classification. The findings imply that the FETech measure is informative not only within technology sectors but also outside them. Overall, we show that FETech identifies meaningful variation in IPO firms' engagement with frontier emerging technologies that is distinct from conventional sector labels.

One limitation of our measure is that it is designed to capture the leading emerging technologies that firms disclose and emphasize at the time of going public, rather than all

technological experimentation occurring inside the firm. Inclusion in the first two stages of Gartner's Hype Cycle (Technology Trigger and Peak of Inflated Expectations stages) indicates that a technology is viewed as a frontier emerging technology at a given point in time, but its eventual adoption path and ultimate commercial impact remain to be seen. Accordingly, FETech should be interpreted as a measure of firms' engagement with frontier emerging technologies at market entry, not as a direct measure of eventual technological success. Understanding why some leading emerging technologies move from experimentation to broad adoption while others fail to commercialize remains an important issue for future research. More broadly, future work could examine how the public-market entry of high-FETech firms affects competitors, incumbents, and industry dynamics, including whether such IPOs intensify competition, reshape valuation across rivals, or accelerate the diffusion of new technologies.

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Figure 1. Construction of FETech from Gartner's Hype Cycle

This figure illustrates the construction of FETech from Gartner's Hype Cycle. The shaded region in the left panel identifies the early-stage technology window used to build the FETech dictionaries, beginning with technologies at the Technology Trigger stage and ending at the Peak of Inflated Expectations. The right panel summarizes the text-based measurement process: Gartner Hype Cycle reports are collected, relevant emerging technologies are extracted and standardized into time-varying dictionaries, IPO prospectuses are preprocessed, and dictionary terms are matched to each prospectus to compute WF-IDF weights. The final FETech measure is scaled by document length to capture each IPO firm's exposure to frontier emerging technologies.

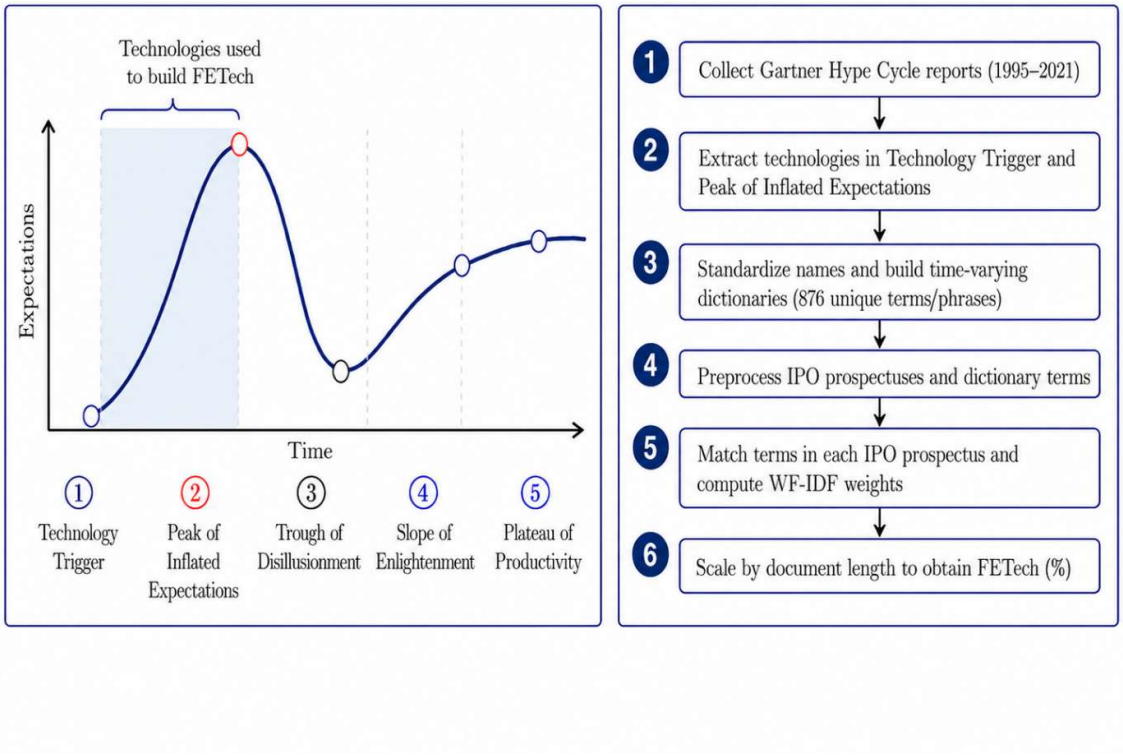


Table 1. Summary statistics for IPO sample, 1994–2021

Summary statistics for IPO sample, 1994–2021. The sample includes 2,467 US IPOs with an offer price of at least $5 per share. Financial variables are obtained by the IPO offering years. All variables excluding dummy ones are converted into percentage. FETech is multiplied by 100 for readability.

Variable	N	Mean	SD	P5	Median	P95
FETech	2,467	0.82	1.50	0.00	0.28	3.44
Patents	2,467	5.58	94.30	0.00	0.00	15.00
Citations	2,467	17.24	70.10	0.00	0.00	90.96
Market return	2,467	0.92	3.37	-4.74	1.17	5.92
Share overhang	2,467	1.10	3.53	0.00	0.00	4.85
Underwriter	2,467	0.69	0.46	0.00	1.00	1.00
EPS	2,467	0.97	0.17	1.00	1.00	1.00
VC	2,467	0.47	0.50	0.00	0.00	1.00
High-tech	2,467	0.68	0.50	0.00	1.00	1.00
Ln(age)	2,467	2.26	0.98	0.69	2.20	4.22
Ln(sales)	2,467	3.47	2.37	0.10	3.81	7.18
R&D	2,467	28.68	31.17	0.00	17.46	78.12
ROA	2,467	-7.59	49.45	-60.22	0.00	26.37
Cash	2,467	30.21	29.16	0.48	20.39	90.46
Leverage	2,467	19.02	39.37	0.00	5.31	72.70
Tobin's Q	2,467	368.77	649.80	6.49	219.79	1,119.13
Tangibility	2,467	16.79	22.26	0.28	6.88	71.24
Bid-ask spread	2,467	14.54	11.94	2.07	10.97	38.51
Ln(volume)	2,467	15.04	1.24	12.96	15.14	16.73
Price revision	2,467	0.02	14.78	-18.03	0.00	12.50
First day return	2,467	25.04	52.86	-10.00	10.53	113.92

Table 2. Correlation matrix

This table reports pairwise Pearson correlations for the IPO sample. The matrix is presented in lower-triangular form. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1) FETech	1.00																				
(2) Patents	0.05*	1.00																			
(3) Citations	0.06***	0.01	1.00																		
(4) Market return	-0.03	-0.01	-0.00	1.00																	
(5) Share overhang	0.02	-0.01	0.09***	0.00	1.00																
(6) Underwriter	-0.01	-0.03	-0.04*	-0.04*	-0.00	1.00															
(7) EPS	0.04*	0.01	0.04*	0.02	0.02	0.01	1.00														
(8) VC	0.08***	-0.00	0.17***	-0.00	-0.02	-0.07***	0.15***	1.00													
(9) High-tech	0.13***	0.03	0.09***	-0.03	-0.03	-0.04*	0.04**	0.22***	1.00												
(10) Ln(age)	-0.03*	0.06***	-0.12***	-0.00	0.01	0.05***	-0.04**	-0.23***	-0.11***	1.00											
(11) Ln(sales)	0.03*	0.09***	-0.09***	0.02	-0.04**	0.09***	0.20***	-0.26***	-0.13***	0.31***	1.00										
(12) R&D	0.11***	0.07***	0.14***	-0.02	-0.04**	-0.03*	0.15***	0.56***	0.27***	-0.15***	-0.30***	1.00									
(13) ROA	-0.12***	0.01	-0.08***	0.02	0.01	0.07***	-0.03*	-0.20***	-0.13***	0.17***	0.39***	-0.41***	1.00								
(14) Cash	0.11***	-0.00	0.13***	0.00	-0.00	-0.11***	0.12***	0.45***	0.20***	-0.26***	-0.38***	0.47***	-0.22***	1.00							
(15) Leverage	0.04*	-0.01	-0.08***	0.01	-0.04*	0.03	-0.00	-0.19***	-0.09***	0.11***	0.13***	-0.15***	-0.31***	-0.24***	1.00						
(16) Tobin's Q	0.15***	-0.01	0.22***	-0.01	0.04**	-0.05**	0.09***	0.21***	0.14***	-0.16***	-0.06***	0.21***	-0.29***	0.23***	0.07***	1.00					
(17) Tangibility	-0.12***	-0.01	-0.09***	-0.00	-0.05**	0.07***	0.06***	-0.26***	-0.11***	0.01	0.33***	-0.33***	0.14***	-0.35***	0.20***	-0.13***	1.00				
(18) Bid-ask spread	0.17***	-0.01	0.14***	-0.01	0.02	-0.07***	0.08***	0.32***	0.17***	-0.22***	-0.19***	0.27***	-0.18***	0.31***	-0.16***	0.28***	-0.21***	1.00			
(19) Ln(volume)	0.19***	0.11***	0.03	0.00	-0.01	0.06***	0.06***	0.10***	0.05***	0.09***	0.37***	0.03	0.09***	-0.03	-0.00	0.12***	0.07***	0.22***	1.00		
(20) Price revision	0.09***	-0.00	0.03	0.06***	0.05**	-0.01	0.01	0.01	0.06***	-0.02	0.03	0.03	0.01	0.01	-0.05**	0.04**	-0.06***	0.07***	0.13***	1.00	
(21) First day return	0.15***	-0.01	0.16***	0.08***	0.13***	-0.02	0.05**	0.19***	0.10***	-0.13***	-0.02	0.11***	-0.04*	0.16***	-0.10***	0.45***	-0.11***	0.43***	0.27***	0.25***	1.00

Table 3. Validation for FETech

Regressions of traditional measures of innovation. The dependent variables are the number of patents (or its natural log), the number of citations per patent (or its natural log), and natural log of R&D. Control variables are Industry effect, High-tech, EPS+, VC, Share overhang, Top underwriter, Ln(Age), Ln(Sales), Book-to-Market, Leverage, ROA, R&D intensity (except model 3). All regressions also include an intercept and calendar year dummies. Standard errors in parentheses are clustered by industry. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Patents Poisson (1)	Citations Poisson (2)	Ln(R&D) OLS (3)
FETech	4.611***	0.792***	3.132**
	(0.730)	(0.305)	(1.563)
Industry Effect	0.013***	0.019***	0.003***
	(0.000)	(0.000)	(0.000)
High-tech	0.054**	0.255***	0.364***
	(0.024)	(0.011)	(0.047)
Year dummies	Yes	Yes	Yes
Adj. R^2	NA	NA	0.464
Obs	2,467	2,467	2,467

Table 4. Frontier emerging technologies and IPO outcomes

Regressions with the first day return, price revision, natural log of trading volume, and bid-ask spread as the dependent variables. All regressions also include an intercept and calendar year dummies. Standard errors clustered by industry are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	First day return	Price revision	Trading volume	Bid-ask spread
	(1)	(2)	(3)	(4)
FETech	251.716***	65.589**	7.418***	42.609**
	(68.302)	(30.721)	(1.015)	(20.730)
Industry effect	0.158**	0.217***	0.256***	0.364***
	(0.070)	(0.076)	(0.038)	(0.047)
High-tech	0.419	0.852	0.026	0.465
	(1.649)	(0.646)	(0.058)	(0.464)
VC	12.913***	-0.296	0.322***	2.727***
	(2.318)	(0.723)	(0.058)	(0.583)
EPS+	-1.347	-0.349	-0.453*	1.937**
	(2.180)	(0.975)	(0.269)	(0.809)
Market return	1.140**	0.332***	0.016**	0.071
	(0.537)	(0.102)	(0.008)	(0.046)
Share overhang	1.484***	0.274	0.010	0.043
	(0.385)	(0.213)	(0.007)	(0.054)
Top underwriter	0.547	-0.048	0.119**	-0.296
	(1.670)	(0.738)	(0.050)	(0.372)
Ln(age)	-3.803***	-0.385	0.037	-1.029***
	(1.377)	(0.298)	(0.047)	(0.271)
Ln(sales)	1.191**	0.278***	0.195***	-0.355***
	(0.504)	(0.088)	(0.022)	(0.101)
Up revision	0.935***		0.000	0.019**
	(0.337)		(0.002)	(0.008)
Year dummies	Yes	Yes	Yes	Yes
Adj. R^2	0.214	0.030	0.362	0.367
Obs	2,467	2,467	2,467	2,467

Table 5. Post-IPO firm policies, performance, valuation and innovation activities

Regressions with post-IPO firm policies or innovation activities as the dependent variable. All regressions also include an intercept, and calendar year dummies. Standard errors clustered by industry are shown in parentheses. The real value of patent is equal to the nominal value deflated to 1982 (million) dollars using the CPI. Control variables include Industry effect, High-tech, EPS+, VC, first day return, Top underwriter, ln(age), ln(total assets), Tangibility, leverage, ROA, and Tobin's Q, excluding the dependent variable in each regression. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Leverage (1)	ROA (2)	Tobin's Q (3)	Cash (4)	Growth (5)	Ln(R&D) (6)	Patents (7)	Citations (8)
$FETech_{(t-1)}$	-161.033***	-261.770***	5.130***	71.290*	3.125*	3.106**	9.246**	4.688***
	(58.431)	(90.040)	(1.889)	(43.158)	(1.607)	(1.485)	(4.461)	(1.680)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.003	0.294	0.324	0.344	0.317	0.624	NA	NA
Obs	2,098	2,098	2,098	2,098	2,098	2,098	2,467	2,467

Table 6. IPO outcomes in subsamples of high technology and non-high technology firms

Regressions with the first-day return, price revision, natural logarithm of trading volume, and bid-ask spread as the dependent variables. All regressions also include an intercept and calendar year dummies. Standard errors in parentheses are clustered by industry. Panel A (B) examines whether the effect of FETech varies for a subsample of high tech (non-high-tech) firm.

Panel A. High-tech firms

	First day return	Price revision	Trading volume	Bid-ask spread
	(1)	(2)	(3)	(4)
FETech	267.258***	58.801**	6.220***	26.329*
	(70.990)	(25.048)	(1.281)	(13.731)
Industry effect	0.140*	0.234***	0.274***	0.345***
	(0.077)	(0.075)	(0.060)	(0.066)
VC	12.195***	-0.921	0.316***	2.649***
	(2.532)	(0.864)	(0.076)	(1.014)
EPS+	-6.306	-0.483	-0.517	2.842***
	(4.693)	(2.820)	(0.340)	(0.573)
Market return	1.294*	0.385***	0.011	-0.008
	(0.690)	(0.118)	(0.009)	(0.051)
Share overhang	1.500***	0.299***	0.013*	0.022
	(0.438)	(0.099)	(0.007)	(0.027)
Top underwriter	0.710	-0.189	0.078	-0.394
	(2.397)	(0.849)	(0.048)	(0.403)
Ln(age)	-4.964***	-0.553	0.028	-0.988**
	(1.872)	(0.485)	(0.065)	(0.422)
Ln(sales)	1.381**	0.418**	0.215***	-0.343**
	(0.609)	(0.194)	(0.026)	(0.139)
Up revision	0.992***		-0.001	0.021**
	(0.348)		(0.002)	(0.008)
Year dummies	Yes	Yes	Yes	Yes
Adj. R^2	0.224	0.028	0.377	0.336
Obs	1,689	1,689	1,689	1,689

Panel B. Non-high-tech firms

	First day return	Price revision	Trading volume	Bid-ask spread
	(1)	(2)	(3)	(4)
FETech	220.683***	90.541***	9.501**	98.331***
	(70.990)	(34.368)	(4.266)	(28.005)
Industry effect	0.205***	0.171**	0.227***	0.382***
	(0.077)	(0.078)	(0.041)	(0.056)
VC	16.521***	1.764*	0.411***	3.088***
	(2.532)	(1.006)	(0.106)	(0.821)
EPS+	5.283	0.316	-0.290	0.841
	(4.693)	(2.075)	(0.205)	(1.661)
Market return	0.890	0.202	0.025*	0.239**
	(0.690)	(0.127)	(0.015)	(0.102)
Share overhang	1.658***	0.160	-0.003	0.264
	(0.438)	(0.226)	(0.027)	(0.181)
Top underwriter	-0.984	0.403	0.196*	0.064
	(2.397)	(0.922)	(0.118)	(0.735)
Ln(age)	-2.193	-0.104	0.054	-1.073***
	(1.872)	(0.386)	(0.049)	(0.308)
Ln(sales)	0.822	0.011	0.156***	-0.390***
	(0.609)	(0.188)	(0.021)	(0.150)
Up revision	0.302		0.007	-0.012
	(0.348)		(0.005)	(0.046)
Year dummies	Yes	Yes	Yes	Yes
Adj. R^2	0.160	0.019	0.347	0.382
Obs	778	778	778	778

Table 7. IPO outcomes controlling for innovation

Regressions with the first-day return, price revision, natural logarithm of trading volume, and bid-ask spread as the dependent variables. All regressions also include an intercept and calendar year dummies. Standard errors clustered by industry are shown in parentheses. Control variables include Industry effect, High-tech, EPS+, VC, first day return, Top underwriter, ln(age), ln(total assets). Innovation is measured by using Li et al. (2021)'s method. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	First day return	Price revision	Trading volume	Bid-ask spread
	(1)	(2)	(3)	(4)
FETech	198.315***	52.638**	5.829***	33.570*
	(71.865)	(21.312)	(1.020)	(17.398)
Innovation	22.984***	5.306*	0.762***	3.567***
	(8.813)	(2.791)	(0.231)	(1.071)
Ln(patents)	-0.651	-0.717	0.101***	0.341
	(0.874)	(0.441)	(0.033)	(0.236)
Ln(citations)	3.039***	0.086	0.009	-0.061
	(0.953)	(0.278)	(0.020)	(0.125)
Ln(R&D)	-0.517	0.410	-0.069**	0.626
	(1.357)	(0.315)	(0.033)	(0.410)
Year dummies	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.220	0.031	0.372	0.370
Obs	2,467	2,467	2,467	2,467

Table 8. Main Results with IPO Cycle Controls

Regressions with the first-day return, price revision, natural logarithm of trading volume, and bid-ask spread as the dependent variables. Control variables include Industry effect, High-tech, EPS+, VC, first day return, Top underwriter, ln(age), ln(total assets). Industry Underpricing(t-1), Industry M/B(t-1) are the industry underpricing and Market-to-Book computed from prior IPO year by using TNIC3-based method. # of IPOs(t-1) is the number of IPOs in an IPO firm industry computed from previous quarter by using TNIC3-based method. All regressions also include an intercept and calendar year dummies. Standard errors clustered by industry are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	First day return (1)	Price revision (2)	Trading volume (3)	Bid-ask spread (4)
FETech	243.885***	64.189*	8.167***	46.890**
	(65.958)	(37.603)	(1.402)	(20.389)
Industry Underpricing(t-1)	0.170	0.057	-0.001	-0.005
	(0.220)	(0.050)	(0.004)	(0.014)
Industry M/B(t-1)	-0.002	-0.000	-0.000	-0.000***
	(0.001)	(0.000)	(0.000)	(0.000)
# of IPOs(t-1)	-4.077***	-0.846*	-0.113**	-0.418**
	(1.289)	(0.510)	(0.054)	(0.201)
Industry effect	0.155**	0.023***	0.003**	0.044***
	(0.069)	(0.008)	(0.001)	(0.012)
High-tech	0.472	0.873	0.015	0.699
	(1.720)	(0.627)	(0.060)	(0.478)
Year dummies	Yes	Yes	Yes	Yes
Adj. R^2	0.215	0.027	0.344	0.352
Obs	2,467	2,467	2,467	2,467

Table 9. Main Results with Sentiment Controls

Regressions with the first-day return, price revision, natural logarithm of trading volume, and bid-ask spread as the dependent variables. All regressions also include an intercept and calendar year dummies. Standard errors clustered by industry are shown in parentheses. Negative and positive sentiment are computed based on a word count method and Loughran and McDonald (2011) dictionary. Control variables include Industry effect, High-tech, EPS+, VC, first day return, Top underwriter, ln(age), ln(total assets). *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A Negative Sentiment

	First day return	Price revision	Trading volume	Bid-ask spread
	(1)	(2)	(3)	(4)
FETech	260.016***	65.198***	7.363***	43.582***
	(67.671)	(20.334)	(1.059)	(16.250)
Negative Sentiment	5.601*	-0.270	-0.037	0.609
	(2.906)	(1.024)	(0.109)	(0.602)
Year dummies	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.214	0.030	0.362	0.367
Obs	2,467	2,467	2,467	2,467

Panel B Positive Sentiment

	First day return	Price revision	Trading volume	Bid-ask spread
	(1)	(2)	(3)	(4)
FETech	243.853***	65.246***	7.348***	41.897**
	(68.539)	(20.292)	(1.022)	(16.623)
Positive Sentiment	21.004**	0.986	0.174	2.931*
	(9.481)	(2.120)	(0.161)	(1.552)
Year dummies	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.217	0.030	0.362	0.368
Obs	2,467	2,467	2,467	2,467

Table 10. IPO outcomes excluding the technology bubble and financial crisis years

Regressions with the first-day return, price revision, natural logarithm of trading volume, and bid-ask spread as the dependent variables. All regressions also include an intercept and calendar year dummies. Standard errors clustered by industry are shown in parentheses. The sample excludes IPOs during the technology bubble period of 1998-1999 and financial crisis years 2008–2009. Control variables include Industry effect, High-tech, EPS+, VC, first day return, Top underwriter, ln(age), ln(total assets). *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	First day return	Price revision	Trading volume	Bid-ask spread
	(1)	(2)	(3)	(4)
FETech	121.748**	54.815**	6.059***	32.391**
	(60.615)	(27.859)	(1.346)	(14.965)
Year dummies	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.252	0.026	0.375	0.353
Obs	1,972	1,972	1,972	1,972

Table 11. Heterogeneity in IPO outcomes

Note: Regressions with the first-day return, price revision, natural logarithm of trading volume, and bid-ask spread. Panel A (B) examines whether the effect of FETech varies for subsamples partitioned at the sample median by IPO age (firm size). Panel C (D) examines whether the effect of FETech varies by patent possession (venture capital investment). All regressions also include an intercept and calendar year dummies. Control variables include Industry effect, High-tech, EPS+, VC, first day return, Top underwriter, ln(age), ln(total assets). Standard errors in parentheses are clustered by industry. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Firm age

	First day return	Price revision	Trading volume	Bid-ask spread
	(1)	(2)	(3)	(4)
FETech	316.543***	110.623**	7.375***	31.671*
	(113.804)	(54.850)	(1.107)	(17.037)
Old	-0.412	0.218	-0.179**	-0.882
	(3.095)	(0.963)	(0.076)	(0.744)
FETech x Old	-167.736	-116.631	-0.045	27.566
	(154.207)	(145.956)	(1.900)	(37.336)
Year dummies	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.214	0.033	0.363	0.367
Obs	2,467	2,467	2,467	2,467

Panel B. Firm size

	First day return	Price revision	Trading volume	Bid-ask spread
	(1)	(2)	(3)	(4)
FETech	257.730***	101.077***	8.766***	63.156*
	(59.528)	(24.603)	(0.905)	(34.458)
Large	10.347***	1.716***	0.647***	-2.272***
	(2.980)	(0.647)	(0.101)	(0.502)
FETech x Large	17.622	-72.684	-0.851	-49.686
	(101.335)	(47.349)	(1.435)	(41.584)
Year dummies	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.220	0.031	0.410	0.376
Obs	2,467	2,467	2,467	2,467

Panel C. Patent possession

	First day return	Price revision	Trading volume	Bid-ask spread
	(1)	(2)	(3)	(4)
FETech	241.325***	78.397*	7.498***	32.577**
	(83.528)	(42.614)	(1.297)	(15.924)
Patent	4.153	-0.879	0.061	0.950
	(4.917)	(0.544)	(0.073)	(0.679)
FETech x Patent	20.271	-33.845	-0.366	26.064
	(126.036)	(31.376)	(2.578)	(41.103)
Year dummies	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.214	0.030	0.362	0.368
Obs	2,467	2,467	2,467	2,467

Panel D. VC backing

	First day return	Price revision	Trading volume	Bid-ask spread
	(1)	(2)	(3)	(4)
FETech	229.195***	87.965**	6.493***	54.420***
	(78.343)	(44.514)	(1.431)	(15.151)
VC	12.485***	0.131	0.304***	2.954***
	(3.079)	(0.641)	(0.062)	(0.845)
FETech x VC	48.338	-48.038*	1.986	-25.109
	(161.039)	(26.136)	(1.617)	(37.882)
Year dummies	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.214	0.030	0.362	0.367
Obs	2,467	2,467	2,467	2,467

Appendix

Table A1. Gartner's Technology Keywords classified into five periods

Year	Technology keywords
1995-2000	asps, audio_mining, avatar, biometric, bluetooth, cable_modem, chatbot, digital_ink, digital_paper, digital_video_disk, dvd, ecash, electronic_ink, emergent_computation, enterprise_portal, intelligent_agent, internet_terminal, internet_tv, intranet, java, knowledge_management, linux, netcaste, online_community, push_technology, quantum_computing, saas, smart_card, speech_analytic, synthetic_character, text_mining, ubiquitous_computing, voice_portal, vrml, wap, wearable_computer, wireless_communication, wireless_web, xdsl, xml
2001-2005	3d_printing, 4_g, 802153a, 802154, 802_16d_wimax, augment_reality, basic_web_service, biometric_identity_document, biometric_user_identification, bpm_suite, brain_interface, business_process_platform, carbon_nanotube, chatbot, commercial_grid, corporate_semantic_web, desktop_linux_business, digital_ink, digital_paper, dna_logic, electronic_ink, etag, external_mpp_grid, fourth_generation_wireless_technology, grid_computing, head_mount_display, identity_service_public, information_extraction, inkjet_manufacturing, inkjet_process, internal_web_service, mesh_network_sensor, micro_fuel_cell, modeldriven_approach, molecular_transistor, nanocomputing, natural_language_search, network_collective_intelligence, nlp_search, p2p_voip, passive_rfid, pda_phone, podcast, prediction_market, proteindna_logic, public_mpp_cluster, quantum_computing, rfid_case, semantic_web, smart_dust, smartphone, social_network_analysis, speech_recognition_mobile, synthetic_character, text_mining, think_recognition, trust_computing_platform, truth_verification, ultrawideband, unify_communication, uwb, web_service, wide_area, wiki, wimedia, zigbee
2006-2010	3d_flat_panel_display, 3d_flat_panel_tv, 3d_printing, 4_g, 4_g_standard, activity_stream, augment_reality, autonomous_vehicle, behavioral_economic, cloud_computing, collective_intelligence, computer_brain_interface, content_analytic, context_delivery_architecture, corporate_semantic_web, dna_logic, ebook_reader, erasable_paper_printing_system, event_drive_architecture, expertise_location_management, extreme_transaction_processing, gesture_recognition, glanceable_display, green_it, human_augmentation, internet_tv, ip_v6, mashup, medium_tablet, microblogging, mobile_robot, modeldriven_approach, offline_ajax, portable_personality, prediction_market, private_cloud_computing, quantum_computing, rss_enterprise, smart_robot, social_analytic, speech_recognition_mobile, speech_speech_translation, speech_translation, speechtospeech_translation, surface_computer, tangible_user_interface, telepresence, teraarchitecture, terahertz_wave, video_search, video_telepresence, virtual_world, web_20, web_platform, wireless_power
2011-2015	3d_bioprinting, 3d_print, 3d_print_organ_transplant, 3d_printing, 3d_scanner, activity_stream, advanced_analytic_w, affective_computing, automatic_content_recognition, autonomous_vehicle, big_datum, bioacoustic_sensing, biochip, brain_computer_interface, byod, citizen_data_science, computer_brain_interface, connect_home, consumer_3d_printing, content_recognition, context_enrich_service, crowdsource, data_science, datum_science, digital_dexterity, digital_security, electrovibration, extreme_info_process_mgmt, gamification, group_buying, html5, human_augmentation, hybrid_cloud_computing, internet_thing, internet_tv, iot_platform, micro_datum_center, mobile_robot, natural_language_question_answering, neurobusiness, nfc_payment, peopleliterate_technology, personal_analytic, prescriptive_analytic, private_cloud_computing, quantify_self, quantum_computing, silicon_anode_battery, smart_advisor, smart_dust, smart_robot, smart_workspace, social_analytic, social_tv, software_define_anything, software_define_security, speech_speech_translation, speech_translation, user_interface, video_analytic_customer_service, virtual_personal_assistant, volumetric_display, volumetric_holographic_display, wearable_ui, wireless_power

Year	Technology keywords
2016-2021	2_way_bmi, 4d_print, 5_g, 80211ax, active_metadata_management, adaptive_machine_learning, affective_computing, ai_assist_design, ai_augment_design, ai_augment_development, ai_augment_software_engineering, ai_drive_innovation, ai_paas, ar_cloud, artificial_general_intelligence, artificial_tissue, augment_data_discovery, augment_intelligence, authenticate_provenance, autonomous_driving_level_5, autonomous_mobile_robot, biochip, biodegradable_sensor, biotech_cultured_tissue, blockchain, blockchain_datum_security, brain_computer_interface, brain_machine_interface, citizen_twin, cognitive_expert_advisor, commercial_uavs, composable_application, composable_enterprise, composable_network, composite_ai, computer_edge, connect_home, context_brokering, conversational_ai_platform, conversational_user_interface, data_broker_paas, datum_fabric, dbrpaas, decentralize_autonomous_organization, decentralize_finance, decentralize_identity, decentralize_web, deep_learning, deep_neural_network_asic, deep_neural_network_deep_learning, deep_reinforcement_learning, differential_privacy, digital_human, digital_op, digital_platform_conductor_tool, digital_twin, digital_twin_person, dna_computing_storage, edge_ai, edge_analytic, edge_compute, embed_ai, emotion_ai, employee_communication_application, exoskeleton, explainable_ai, fly_autonomous_vehicle, generalpurpose_machine_intelligence, generative_adversarial_network, generative_ai, gesture_control_device, health_passport, homomorphic_encryption, human_augmentation, immersive_workspace, industry_cloud, influence_engineering, iot_platform, knowledge_graph, light_cargo_delivery_drone, low_cost_single_board_computer_edge, low_earth_orbit_satellite_system, machine_learning, machine_readable_legislation, micro_datum_center, mobile_robot, multiexperience, name_datum_network, nanoscale_3d_printing, neural_network_deep_learning, neuromorphic_hardware, nft, nonfungible_token, package_business_capability, personal_analytic, personification, physics_inform_ai, private_5_g, quantum_computing, quantum_machine_learning, quantum_ml, real_time_incident_center_aas, responsible_ai, sase, secure_access_service_edge, self_heal_system_technology, self_integrate_application, self_supervise_learn, serverless_paas, smart_datum_discovery, smart_dust, smart_robot, smart_workspace, social_datum, social_distancing_technology, software_define_security, sovereign_cloud, synthetic_datum, transfer_learning, virtual_assistant, virtual_personal_assistant, volumetric_display

Note. *Keywords cover the Technology Trigger and Peak of Inflated Expectations stages of the Gartner Hype Cycle. Within each period the list is de-duplicated and sorted alphabetically; spelling and transcription errors have been corrected. Generic single words and partial sub-phrase fragments generated by the n-gram expansion have been removed so the table contains only specific technology keywords; a technology may recur across periods.*

Generic words removed: *1995-2000: interactive; 2001-2005: analytic, architecture, computer, group, interface, network, pallet, payment, personal; 2006-2010: ambient, architecture, broker, control, display, environment, service; 2011-2015: image; 2016-2021: drone, ml*

Appendix A2. Examples of language in IPO prospectuses with high FETech

Panel A: IPO firms with FETech in top decile that filed no patents before IPO	
Firm	**Language in prospectus**
WEBSITE PROS INC	We are a leading provider of Web services and products that enable small and medium-sized businesses to establish, maintain, promote and optimize their Internet presence. Through the combination of our proprietary Website publishing and management software, automated workflow processes, and specialized workforce development and management techniques, we believe we achieve production efficiencies that enable us to offer sophisticated Web services at affordable rates. We currently rely primarily on a combination of copyright, trade secret and trademark laws, confidentiality procedures, contractual provisions, and other similar measures to protect our proprietary information. Due to the rapidly changing nature of applicable technologies, we believe that the improvement of existing offerings, reliance upon trade secrets and unpatented proprietary know-how and development of new offerings.
MUSICMAKER.COM	Musicmaker.com is a leading e-commerce provider of customized music CD compilations over the Internet. Our customers can search our extensive online music library and sample and select songs to make their own customized compilation CDs. Our music library currently contains over 150,000 licensed song titles. Our custom CDs can be further personalized by including selected graphics or consumer provided text. Our custom CDs have sound quality equivalent to pre-recorded CDs available at retail stores and are sold at competitive prices. We manufacture and ship our custom CDs from our state-of-the-art production facility generally within 24 hours of order. Our proprietary technology (patent application allowed) can digitally store approximately five million songs, provides advanced search/retrieval capabilities and automates the high-speed production of our custom CDs. Customers can also download music from our music library using either Secure-MP3, a copyright-protected format, or a Liquid Audio, Inc. format.
CALAMOS ASSET MANAGEMENT	Calamos Asset Management, Inc. provides investment advisory services through its subsidiaries to institutions and individuals, principally in the United States, managing $32.3 billion in client assets. Our investment approach demands specific requirements for all aspects of the investment process, including risk management, security analysis and trade processing. Our use of in-house technology and software, in particular our proprietary Calamos Corporate System, is a result of this view, enabling customization of systems across our company. Extending beyond the proprietary software used by our investment team, all of our internal systems are geared to the underlying assumptions that gird the investment process, allowing for a more seamless integration of security analysis, trade processing, accounting, and the portfolio administration of almost 25,000 separately managed accounts. Because of this integrated approach, our quantitative analytics can assess securities in a way that we believe is more sophisticated than that of many of our competitors.

Panel B: IPO firms with FETech in top decile that filed patents before IPO	
Firm	**Language in prospectus**
KINTERA INC	We currently have one issued patent and 16 pending patent applications in the United States. We may not be successful in obtaining these patents and we may be unable to obtain additional patent protection in the future. In addition, any issued patents may not provide us with any competitive advantages, or may be challenged by third parties. We are a leading provider of software that enables nonprofit organizations to use the Internet to bring their employees, volunteers and donors together in online, interactive communities that increase donations, reduce fundraising costs and build affinity for an organization's cause. Kintera Sphere is an enterprise-grade software system that integrates a suite of features, including content management, contact management, communication, commerce, community and reporting, all of which are built on a unified database and payment processing engine. We offer our software as a service that customers access with a web browser.
HYBRID NETWORKS	The Company currently has two patents issued in the United States, as well as pending patent applications in the United States, Europe and Japan that relate to its network and modem technology and the communication processes implemented in those devices. In the future, the Company intends to seek additional United States and foreign patents on its technology. Hybrid's objective is to be a leader in providing cost-effective, high speed Internet and intranet access solutions to cable system operators, broadband wireless system operators, ISPs and other businesses. The Series 2000 also facilitates the entrance of broadband wireless system operators into the high-speed Internet access market. The Series 2000 has been designed to utilize an array of wireless frequencies, ranging from UHF to MMDS frequencies, and to minimize commonly experienced interference problems.
FAROUDJA INC	Yves Faroudja, the Company's founder and Chief Technical Officer, personally holds or was assigned 44 U.S. and 6 foreign patents, and 6 U.S. and20 foreign patent applications, which have been licensed to the Company, and on which the Company depends for the enhancement of its current products and the development of future products. Faroudja designs, develops and markets video image enhancement products that significantly improve images to achieve cinema-like quality. Faroudja's technology, experience and reputation for providing sophisticated video processing products will enable it to address opportunities in the emerging Digital Television (DTV) and High Definition Television (HDTV) broadcast environment and in the converging Personal Computer (PC) and TV markets.

Table A.3. Variable definitions

Variable	Definition	Source
Independent variable of interest		
FETech	The weighted frequency of frontier emerging technology-related words in the IPO prospectus, measured as the number of such words divided by the total number of words in the prospectus and adjusted to assign lower weight to more common terms. (%)	Prospectus
Dependent variable		
First day return	The percentage change from the offering price to the closing price on the first day of trading	SDC
Price revision	The percentage change from the midpoint of the anticipated price range provided in the IPO prospectus to the actual offering price.	SDC
Ln(volume)	Natural logarithm of trading volume on the first trading day	CRSP
Bid-ask spread	The percentage difference between the ask price and bid price divided by the average of closing bid and ask prices	CRSP
Long run abnormal return	Cumulative percentage abnormal return on the IPO stock over the 12 months after the first post-IPO trading date, computed using monthly DGTW benchmark portfolio returns, as in Daniel et al. (1997)	CRSP
Volatility	Standard deviation of monthly stock returns over 12 months after IPO trading dates.	CRSP
Patents	The number of patents filed before or after IPO dates	Noah Stoffman's website
Citations	The number of forward citations per patent	Noah Stoffman's website
Patent value (Nominal)	Value of patent in millions of nominal dollars	Noah Stoffman's website
Patent value (Real)	Value of patent deflated to 1982 (million) dollars using the CPI	Noah Stoffman's website
Control variables		
Industry effect	Industry-year average of the dependent variable within the firm's TNIC3-defined product-market industry, including the firm itself.	Hoberg and Phillips' website

High-tech	One if the IPO firm is classified as high-tech based on the combined SIC- and TNIC3-based procedure, and zero otherwise.	Hoberg and Phillips' website
Up revision	The percentage difference between offer price and mid filing price if offer price is larger than mid filing price, else zero	SDC
Age	Firm age = IPO year – Firm founding year	SDC, Jay Ritter's website
VC	One if IPO is backed by venture capital, else zero	SDC
	One if IPO is high technology firm, else zero	SDC
EPS+	One if IPO has a positive earnings per share, else zero	SDC
Top underwriter	One if IPO has an underwriter ranked in the top 8 in Jay Ritter's list, else zero	SDC, Jay Ritter's website
Market return	Buy-and-hold percentage return on CRSP Nasdaq value-weighted index on the 15-trading days prior to the IPO date	CRSP
Share overhang	The number of shares retained by pre-existing owners divided by the number of shares in the initial offering (%)	SDC
BM	Book value of common equity divided by market value of common equity (%)	COMPUSTAT
Sales	Natural log of firm sales in million dollars	COMPUSTAT
R&D	R&D spending divided by total assets, xrd/at (%)	COMPUSTAT
ROA	EBITDA divided by total assets, ebitda/at (%)	COMPUSTAT
Leverage	Long-term debt plus debt in current liabilities divided by total assets, (ldtt + dlc) / at (%)	COMPUSTAT
Tobin's Q	Computed as: ((prcc_f * csho) +pstk+dltt+dlc) / at	COMPUSTAT
Total assets	Natural log of total assets	COMPUSTAT
Tangibility	Property, plant, and equipment divided by total assets, ppent/at (%)	COMPUSTAT
Growth	Sales growth in five years after IPO year	COMPUSTAT
Negative sentiment	Percentage of negative words using Loughran and McDonald (2011) dictionary	Prospectus
Positive sentiment	Percentage of positive words using Loughran and McDonald (2011) dictionary	Prospectus
Innovation	The weighted-frequency of innovation-related words in IPO prospectus, i.e., the number of innovation-related words divided by the total number of words in a prospectus, adjusted to reduce the weight of more frequent words following Li et al. (2021). (%)	Prospectus